Dundee Discussion Papers in Economics 298

Allanson, Paul

Publication date:
2017

Document Version
Publisher's PDF, also known as Version of record

Dundee Discussion Papers
in Economics

Accounting for differences in population health between the regions of the United Kingdom: a new measurement framework for ordinal data

Paul Allanson

Department of
Economic Studies
University of Dundee
Dundee
DD1 4HN

Working Paper
No. 298
July 2017
ISSN: 1473-236X

Accounting for differences in population health between the regions of the United Kingdom: a new measurement framework for ordinal data

Paul Allanson
Economics Studies, University of Dundee School of Business, United Kingdom.
Email: p.f.allanson@dundee.ac.uk

***Abstract**: The paper investigates the association between regional health outcomes and socioeconomic characteristics in the United Kingdom (UK), based on a recently proposed measure of the degree to which the populations of different regions occupy well-defined strata in the national health distribution. The headcount index of health stratification is well-defined even if only ordinal health data are available and has a straightforward interpretation as the population-weighted mean difference in the probabilities that the healthier of any randomly chosen pair of individuals will be from the region with the better rather than the worse population health. The paper provides alternative aggregate decompositions of the index based on the construction of counterfactual distributions using indirect and direct standardisation techniques, with the indirect aproach also providing the basis for a detailed decomposition of the composition effect. The empirical study shows that health stratification is largely due to differences in the socioeconomic and demographic composition of regions rather than in regional health outcomes conditional upon individual-level sociodemographic characteristics, with age, ethnicity and qualifications all more important factors than income.*

Keywords: health stratification; regional analysis; decomposition analysis; ordinal data

JEL classifications: D63, I14, I18

Acknowledgements: The author bears sole responsibility for the further analysis and interpretation of the Family Resources Survey data employed in this study.

1. Introduction

Empirical work on the causes of regional differences in population health outcomes has focused very largely on cardinal measures such as life expectancy and prevalence rates (e.g. the percentage of the population with a disability), with evidence on regional disparities in ordinal or categorical measures of self-reported health and subjective well-being both more limited and equivocal in nature.[1] For example, there has been a long-running debate as to why mortality rates have been persistently higher in West Central Scotland than in similarly deprived regions of Great Britain and Europe (the so-called 'Scottish' or 'Glasgow' effect), but little attention has been paid to the possible explanation of comparable or higher levels of self-reported measures of general health (see Taulbut et al., 2013). One explanation for this particular focus has been the greater availability of routine cardinal health data from administrative sources, such as death certificates and medical registries, but this is no longer such an issue with the introduction in many countries of regular, large-scale, nationally representative sample surveys incorporating questions on health and well-being. A second more general problem has been the question of how to measure health inequalities using ordinal health data without first having to convert them into cardinal form by assigning some more or less arbitrary numerical values either to each response category or to the differences between categories (see Allison and Forster, 2004; Lv et al., 2015; Kobus, 2015).

The main aim of this paper is to develop a framework to investigate the association between regional health outcomes and socioeconomic characteristics that is directly applicable to ordinal health data. Allanson (2017a) has recently sought to address this issue by proposing

[1] For expositional purposes we will use 'health' to refer to both health and wellbeing, drawing a distinction between the two concepts only when it is helpful to do so. World Health Organization (1948) defines health as "a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity."

a new headcount measure of income-related health stratification, which is equal to the population-weighted mean difference in the probabilities that the healthier of any two randomly chosen individuals will be from the more rather than less prosperous region from which they are drawn. The index satisfies a health status exchange condition akin to the Pigou-Dalton principle of transfers in inequality analysis, providing a measure that is equal to twice the between-region generalised health concentration index for binary health status indicators but is also well-defined for polytomous categorical variables. The index differs from conventional measures of between-region health inequality in that it takes into consideration the degree of variation in health outcomes within as well as between regions. But it fails to also take account of income variation within regions and may therefore capture not only differences in economic prosperity between regions, given the well-known socioeconomic gradient in health, but also systematic differences in health conditional upon income. For example, Marmot at al. (2010, Figure 2.9) shows that if one compares neighbourhoods with the same level of income deprivation then disability-free life expectancy is lower in some regions of England than in others at all levels of neighbourhood income deprivation.

This paper adopts an alternative approach based on a measure of the total level of health stratification between regions, where the total and income-related measures are related in the same way as the health Gini and concentration indices. Specifically, the headcount index of health stratification is equal to the population-weighted mean difference in the probabilities that the healthier of any randomly chosen pair of individuals will be from the region with the better rather than worse population health. The aggregate decomposition of this index serves to identify how much of total health stratification is due to differences in the socioeconomic and demographic composition of regions and how much to regional differences in health outcomes conditional upon individual-level sociodemographic characteristics. We provide alternative estimators of this aggregate decomposition based on the construction of

counterfactual distributions using either indirect (Chernozhukov et al., 2013) or direct (DiNardo et al., 1996) standardisation techniques, with the former also providing the basis for a detailed decomposition to identify the individual contributions of differences in the regional distributions of each individual-level characteristic – age, sex, ethnicity, income and qualifications – to total stratification.

Our measurement of the degree of stratification between the population health distributions of the regions of a country contrasts with the conventional focus in health inequalities research on "the evaluation of the inequality in the distribution of health status across individuals in a population" (Allison and Foster, 2004, p.505). Our methodological framework further differs from most of the literature on the measurement of health inequality with ordinal data in that it incorporates the socioeconomic dimension, with the seminal paper by Allison and Foster (2004) emphasising the point that their method is designed to evaluate overall inequality in health, without focusing on any particular cause or justification.

One major exception is Zheng (2011) who compares socioeconomic inequality in health between pairs of regions. Specifically he applies a set of welfare dominance and inequality ordering conditions to health state by income quantile contingency tables for the two regions and thereby provides a comparison of the two health profiles at similar ranks in the income distribution of each region. In contrast our methodology is motivated by the notion of statistical preference (De Schuymer et al., 2003), which provides a 'graded' alternative to stochastic dominance (De Baets and De Mayer, 2007) that yields both a complete ordering of regions and a readily intelligible measure of the differences in population health between them. The further identification of compositional and conditional health effects provides a basis for the comparison of regional health profiles controlling more generally for both socioeconomic and demographic characteristics.

The new measurement framework is used to investigate the association between regional health outcomes and socioeconomic characteristics in the United Kingdom (UK), making use of the responses to the self-reported health questions included in the Family Resources Survey 2014-15. The next two sections provide a discussion of the specification and properties of the headcount stratification index and outline the set of decomposition procedures. The empirical study is presented in Section 4. The final section summarises the contribution and offers some suggestions for further applications of the measurement approach.

2. Measurement of headcount health stratification

Key to our approach is the idea that stratification, unlike segregation, implies a hierarchical ordering of regions, which for the measurement of total health stratification will be by some measure of population health status. If health was cardinally measurable then, following Allanson (2017b), this ordering might be in terms of equally distributed equivalent health, which reduces to ranking regions in order of population mean health in the absence of inequality aversion. However, if the health measure is ordinal then this criterion is inoperable and some other basis must be found for the comparative evaluation of population health across regions. Dubois et al. (2003) have shown axiomatically that only so-called likelihood dominance rules can serve this purpose if population health preferences are characterised by ordinal invariance. More specifically, population health in one region may be said to be statistically preferred (De Schuymer et al., 2003) to that in another if the (strictly) healthier of any randomly matched pair of individuals from the two regions is more likely to be from the first than the second region, with this criterion also providing the basis for our pairwise measure of differences in regional population health. The headcount stratification index is obtained by aggregating over all pairs of regions to yield a national population-weighted average of the absolute values of the pairwise indices.

2.1 Pairwise ranking of regions

Consider some country that consists of $R \geq 2$ mutually exclusive and exhaustive administrative regions. The population size and share of region r $(r = 1,....R)$ are given as n_r and $p_r = n_r / N$ respectively, where $N = \sum_r n_r$ is the national population size.

Population health in region r is a vector of the form $H_r = (h_{1r}, \cdots, h_{n_r r})$, where h_{ir} is the health status of the i'th person, and the national distribution of health $H_U = (H_1, H_2, \ldots H_R)$ is obtained as the union over all regions. Preferences over individual health outcomes are assumed to be complete such that it will be possible to compare the health of any pair of individuals and thereby determine whether the health of one is better, the same or worse than that of the other. We denote the probability that the health of a randomly chosen individual from region r' is at least as good as that of an individual chosen at random from region r as $\mathrm{P}(H_{r'} \geq H_r)$ and from the whole country (including region r' itself) as $\mathrm{P}(H_{r'} \geq H_U) = \sum_r \mathrm{p}_r \, \mathrm{P}(H_{r'} \geq H_r)$.

Preferences over regional population health outcomes are assumed to be reflexive and characterised by ordinal invariance (Dubois et al., 2003). Ordinal invariance implies that, for any pair of regions r and r', changes in individual health outcomes that preserve the ranking of all individuals in the combined health distribution of the two regions will not affect whether population health in r' is judged to be better, the same or worse than in r. Hence, it will be possible to compare population health in the two regions even if health is only ordinal measurable since all that is required is a total preorder on individual health. Dubois et al. (2003, Theorem 1 corollary) prove that the only basis for such a comparison will be a so-called likely dominance rule, which in our case takes the form of the probability-based dominance rule that population health in r' is better, the same or worse than in r if $\mathrm{P}(H_{r'} \geq H_r)$ is respectively greater, the same or less than $\mathrm{P}(H_r \geq H_{r'})$. Thus, for example, population health in r' can only

be judged to be better than in *r* if a randomly chosen individual from *r′* is more likely to have no worse (i.e. the same or better) rather than no better (i.e. the same or worse) health than a randomly chosen individual from *r*. Following De Schuymer et al. (2003) we will say that $H_{r'}$ is statistically preferred to H_r in this case.

Weak statistical preference provides a generalisation of weak first-degree stochastic dominance, since the latter implies the former, but not vice versa (De Baets and De Mayer, 2007). Statistical preference will always provide a complete ranking of all pairs of regions whereas stochastic dominance may not (De Schuymer et al., 2003). The resultant ordering will only be transitive if the probability relationship between the set of regions exhibits mutual rank transitivity (De Baets et al., 2010),[2] but this condition is not required for the construction of our headcount stratification index as it is defined as a weighted average of pairwise indices. If the population health of the two regions are statistically indifferent (e.g. if the health distributions of the two regions are identical) then the index to be considered below will equal zero irrespective of the ordering of the regions.

2.2 Measurement of population health differences between pairs of regions

Let the difference in population health between any two regions *r* and *r′* be defined in the manner of Lieberson (1976) by the pairwise index:

$$\begin{aligned}\Delta_{rr'} &= \mathrm{P}\left(H_{r'} \geq H_r\right) - \mathrm{P}\left(H_r \geq H_{r'}\right) \\ &= \left(\mathrm{P}\left(H_{r'} > H_r\right) + 0.5\,\mathrm{P}\left(H_{r'} = H_r\right)\right) - \left(\mathrm{P}\left(H_r > H_{r'}\right) + 0.5\,\mathrm{P}\left(H_r = H_{r'}\right)\right) \\ &= 1 - 2\left(\mathrm{P}\left(H_r > H_{r'}\right) + 0.5\,\mathrm{P}\left(H_r = H_{r'}\right)\right).\end{aligned} \tag{1}$$

$\Delta_{rr'}$ is thus equal to the difference in the probabilities that a randomly chosen individual from region *r′* will have no worse rather than no better health than a randomly chosen individual

[2] For example, if $H_r = (5,2,2)$, $H_{r'} = (3,3,3)$ and $H_{r''} = (4,4,1)$, where higher scores imply better health, then $\mathrm{P}(H_{r'} > H_r) = 2/3$, $\mathrm{P}(H_{r''} > H_{r'}) = 2/3$ and $\mathrm{P}(H_r > H_{r''}) = 5/9$.

from region *r*. Alternatively, since $\mathrm{P}\left(H_{r'} \geq H_r\right) - \mathrm{P}\left(H_r \geq H_{r'}\right) = \mathrm{P}\left(H_{r'} > H_r\right) - \mathrm{P}\left(H_r > H_{r'}\right)$, $\Delta_{rr'}$ may be interpreted as the difference in the chances that a randomly chosen individual from region r' will have (strictly) better rather than worse health than a randomly chosen individual from region *r*. $\Delta_{rr'}$ is defined for both continuous and discrete health distributions, with the second line of (1) making explicit one possible treatment of ties in the case that $\mathrm{P}\left(H_r = H_{r'}\right) \neq 0$, which will be the norm with self-reported health data from surveys in which individuals are typically asked to choose between a finite number of descriptive categories (e.g. very poor, poor, fair, good, excellent). Thus, importantly, $\Delta_{rr'}$ is well defined even if only ordinal health data are available: for example $\Delta_{rr'} = (0.36 - 0.16) = 0.2$ if health is given by a binary variable with 40% and 60% respectively of the region *r* and r' populations reporting good health. The final line of (1) follows by definition.

$\Delta_{rr'}$ offers a readily intelligible measure of the difference in population health between the two regions that is consistent with the statistical preference criterion used to rank them. In particular, $\Delta_{rr'}$ takes a value of zero if the population health of the two regions are statistically indifferent, although this does not necessarily imply that the health distributions of the two regions are identical, a maximum value of one when the least healthy individual in region r' is strictly healthier than the healthiest individual in region *r*, and a minimum value of minus one when the opposite condition holds. Moreover, it follows that:

$$\Delta_{Ur'} = \mathrm{P}\left(H_{r'} \geq H_U\right) - \mathrm{P}\left(H_U \geq H_{r'}\right) = \sum_{r=1}^{R} p_r \left(\mathrm{P}\left(H_{r'} \geq H_r\right) - \mathrm{P}\left(H_r \geq H_{r'}\right)\right) = \sum_{r=1}^{R} p_r \Delta_{rr'} \qquad (2)$$

provides a summary measure of the population health of region r' compared to the country as a whole, with this measure taking a population-weighted average of zero across all regions, i.e. $\sum_{r'} p_{r'} \Delta_{Ur'} = 0$.

2.3 Definition and properties of the headcount stratification index

$\Delta_{rr'}$ provides a directional measure in the sense of Dagum (2007) with $\Delta_{rr'} = -\Delta_{r'r}$ by definition. Following Allanson (2017b), we note that $|\Delta_{rr'}|$ captures the extent to which the populations of the two regions occupy well-defined strata in their combined health distribution. Specifically, $|\Delta_{rr'}|$ may be interpreted as an identification or classification index that reflects the success with which regional identity can be determined by assuming that the healthier individual of any randomly matched pair will be from the region with the better rather than worse population health. The headcount stratification index *S* is obtained as the population-weighted average of the pairwise stratification indices $|\Delta_{rr'}|$:

$$\begin{aligned} S &= \sum_{r=1}^{R}\sum_{r'=1}^{R} p_r p_{r'} |\Delta_{rr'}| = \sum_{r=1}^{R}\sum_{r'=1}^{R} p_r p_{r'} \left|\mathrm{P}\left(H_{r'} > H_r\right) - \mathrm{P}\left(H_r > H_{r'}\right)\right| \\ &= \sum_{r=1}^{R} p_r \left(\sum_{r'=1}^{R} p_{r'} |\Delta_{rr'}|\right) = \sum_{r=1}^{R} p_r S_r \end{aligned} \tag{3}$$

where $p_r p_{r'}$ may be interpreted as the probability that the first of two individuals randomly selected with replacement from the national population will be from region *r* and the second from region *r′*, and which therefore sum to one over all possible combinations. *S* is invariant to the permutation of regions and to the replication both of the subpopulations within regions (holding the population shares of the regions constant) and of the regions (holding the subpopulations within each region constant). Moreover, the pairwise indices $|\Delta_{rr'}|$ may be meaningfully aggregated, given symmetry, to yield estimates S_r of the contribution of each region to *S*, with the further potential to identify the characteristics or factors that contribute to stratification.

S measures the mean difference in the probabilities that the healthier of two randomly chosen individuals will come from the region with the better rather than worse population health in pairwise comparisons. *S* will take a minimum value of zero if all pairwise indices $|\Delta_{rr'}|$ are zero, implying statistical indifference between the population health of all regions in the country. *S* is strictly increasing in $|\Delta_{rr'}|$, taking a maximum value of $\left(1-\sum_r p_r^2\right)$ if there

is perfect stratification in the sense of Lasswell (1965) with the complete separation of the regional populations into discrete layers in the national health distribution. Dividing S by $\left(1-\sum_r p_r^2\right)$ yields a normalised index $\hat{S}$ that is the population-weighted mean level of pairwise stratification between all mutually distinct regions, taking values in the unit interval.

S is a unit free measure that is invariant to rank-preserving transformations of individual health outcomes. If the health outcome measure is given by a binary indicator variable, taking values of zero and one, then $S = 2\mu G_B = \sum_r \sum_s p_r p_s \left|\mu_s - \mu_r\right|$, i.e. twice the conventional between-region absolute Gini index where $\mu = \sum_r p_r \mu_r = \sum_r p_r P(H_r = 1)$ may be interpreted as a measure of national mean health and G_B is the between-region health Gini index. But unlike the between-region (absolute) Gini index, S is also defined for polytomous categorical variables without the need to first impose some essentially arbitrary cardinalisation of the health measure.

Following Allanson (2017a) it is easy to show that S satisfies a health status exchange condition which holds that an exchange in health status (and hence of ranks in the national health distribution) between an individual from a healthier region and an individual in no better (i.e. the same or worse) health from a less healthy region will not lead to an increase in headcount stratification provided that the exchange does not affect the ordering of regions. In contrast, a simple transfer of health between the two individuals may increase headcount stratification since, for example, the identification of the healthier region might not change as a result while that of the less healthy region could increase in relation to even less healthy regions. Moreover, it is readily apparent that improving the health of the least healthy region, let alone the health of the least healthy individuals in that region, will not necessarily have the most impact on headcount stratification: indeed S is invariant to changes in the health of individuals in the least healthy region whose health is worse, and remains worse, than the most unhealthy individual in any other region. In contrast, it would be sufficient to simply target

health improvements at the least healthy region to have maximum impact on between-region health inequality assuming this was quantifiable.

3. Decomposition of the headcount index

Headcount stratification may reflect differences both in the socioeconomic and demographic composition of regions and in regional health outcomes conditional upon these individual-level characteristics. The separate contributions of compositional and conditional health differences to stratification can be identified using either indirect or direct standardisation techniques to construct a counterfactual distribution that provides the basis for the decomposition of the headcount index. Let $F_{H_U}(h) = P(H_U \leq h) = \sum_r p_r F_{H_r}(h)$ be the observed cumulative distribution function (cdf) of health outcomes for the country as a whole, where $F_{H_r}(h) = P(H_r \leq h)$ is the cdf of health in region *r*. Defining the (joint) distributions $F_{X_U}(x)$ and $F_{X_r}(x)$ analogously for some vector of sociodemographic characteristics $x = (x_1, x_2, \ldots x_K)$, it may be noted that $F_{H_r}(h) = \int F_{H_r|X_r}(h \mid X = x) dF_{X_r}(x)$ where $F_{H_r|X_r}(h \mid X = x)$ is the conditional cdf of health given sociodemographic characteristics in region *r*.

3.1 Indirect standardisation

The indirect standardisation counterfactual is given by the distribution of health outcomes that would be observed if the conditional distribution of health was the same in each region as in the country as a whole. This may be written as:

$$F_{H_U^I}(h) = \sum_{r=1}^{R} p_r F_{H_r^I}(h) = \sum_{r=1}^{R} p_r \left[\int F_{H_U|X_U}(h \mid X = x) dF_{X_r}(x) \right] \quad (4)$$

where $F_{H_U^I}(h)$ and $F_{H_r^I}(h)$ respectively denote the national and regional counterfactual unconditional health distributions, and $F_{H_U|X_U}(h \mid X = x)$ is the national conditional distribution of health. We use the distribution regression approach of Chernozhukov et al.

(2013) to estimate $F_{H_U|X_U}(h \mid X = x) = \Lambda\left(X\beta_U(h)\right) = \Lambda\left(z\right)$, where $\Lambda\left(X\beta_U(h)\right)$ is a chosen link function and $\beta_U(h)$ is a vector of parameters. Specifically, the link function is estimated for each distinct health state *h* (*h*=1,… *W*) observed in the national sample by creating a dummy dependent variable that takes a value of one if the observation on H_U is no better than *h* and zero otherwise. The counterfactual unconditional distribution $F_{H_r^I}(h)$ for each region is then obtained by averaging the predicted probabilities over all observations in that region. Our preferred link function is the standard normal cdf $\Phi\left(z\right)$ but results are also generated using the linear probability model (LPM) to investigate the sensitivity of the findings to the functional specification.

The next step is to construct a set of indirectly standardised pairwise indices $\Delta^I_{rr'} = \mathrm{P}\left(H^I_{r'} > H^I_r\right) - \mathrm{P}\left(H^I_r > H^I_{r'}\right)$ using the counterfactual health distributions, from which it follows immediately that $\Delta^I_{Ur'} = \sum_r p_r \Delta^I_{rr'}$. The aggregate decomposition (cf. Fortin et al., 2011) of the headcount stratification index is defined as:

$$S = \sum_{r=1}^{R}\sum_{r'=1}^{R} p_r\, p_{r'} \left|\Delta_{rr'}\right| = \sum_{r=1}^{R}\sum_{r'=1}^{R} p_r\, p_{r'} \left\{\left|\Delta^I_{rr'}\right| + \left(\left|\Delta_{rr'}\right| - \left|\Delta^I_{rr'}\right|\right)\right\} = S^I + \left(S - S^I\right) \quad (5)$$

where the indirectly standardised index S^I provides a measure of the 'explained' component of total health stratification that is due to compositional differences. The 'unexplained' component due to conditional health differences is captured by the difference ($S-S^I$), which may be either positive or negative. Specifically, if a separate model $F_{H_r|X_r}(h \mid X) = \Lambda\left(X\beta_r(h)\right)$ was estimated for each region then ($S-S^I$) would reflect differences between $\beta_U(h)$ and the set of parameter vectors $\beta_r(h)$, and also, if the link function was non-linear, non-zero average prediction errors by region and health state. We note that if the distribution regression model has no explanatory power then $S^I = 0$, implying that all stratification is due to conditional health differences between regions.

The indirectly standardised index S^I may be further decomposed to yield estimates of the individual contribution of differences between the regional distributions of each

sociodemographic characteristic. Assigning average ranks to ties, we note that $\Delta^I_{rr'} = \bar{F}^I_{r'r} - \bar{F}^I_{rr'} = 1 - 2\bar{F}^I_{rr'}$ where $\bar{F}^I_{rr'} = 1 - \bar{F}^I_{r'r}$ is the average rank of an individual from region r in the region r' counterfactual distribution. Specifically, $\bar{F}^I_{rr'} = \sum_h P\left(H^I_r = h \mid R = r\right)\bar{F}^I\left(h \mid R = r'\right)$ where, for the counterfactual distribution H^I_U, $P\left(H^I_r = h \mid R = r\right)$ is the probability that an individual from region r is in heath state h and $\bar{F}^I\left(h \mid R = r'\right)$ is the average rank of individuals from region r' in health state h. As $\bar{F}^I_{rr} = 0.5$ by definition it follows that $\Delta^I_{rr'} = 2\sum_h P\left(H^I_r = h \mid R = r\right)\left(\bar{F}^I\left(h \mid R = r\right) - \bar{F}^I\left(h \mid R = r'\right)\right)$, which shows that the pairwise index is equal to twice the weighted average difference in ranks. Hence if the distribution regression is given by the LPM then $\Delta^I_{rr'} = 2\sum_h P\left(H^I_r = h \mid R = r\right)\left(\bar{X}_r - \bar{X}_{r'}\right)\beta^*_U\left(h\right)$ where $\bar{X}_r$ and $\bar{X}_{r'}$ are vectors of regional mean characteristics, $\beta^*_U\left(h = 1\right) = \beta_U\left(h = 1\right)/2$ for the worst observed health state, $\beta^*_U\left(h = W\right) = \beta_U\left(h = W - 1\right)/2$ for the best health state, and $\beta^*_U\left(h\right) = \left(\beta_U\left(h\right) + \beta_U\left(h - 1\right)\right)/2$ otherwise. This pairwise decomposition is exact but not symmetric, i.e. the contribution of the regional difference in means for any particular characteristic x_k $(k = 1, \ldots K)$ to $\Delta^I_{rr'}$ will not be the same as to $\Delta^I_{r'r}$. The detailed decomposition is based on the average of these two estimates since S^I is obtained by aggregation over all pairs of regions:

$$\begin{aligned} S^I &= \sum_{r=1}^R \sum_{r'=1}^R p_r p_{r'} \left|\Delta^I_{rr'}\right| \\ &= 2\sum_{r=1}^R \sum_{r'=1}^R p_r p_{r'} \operatorname{sgn}\left(\Delta^I_{rr'}\right)\left(\sum_h P\left(H^I_r = h \mid R = r\right)\left(\bar{X}_r - \bar{X}_{r'}\right)\beta^*_U\left(h\right)\right) \end{aligned} \tag{6}$$

where the sign function takes a value of 1 if $\Delta^I_{rr'} \geq 0$ and –1 otherwise. For the probit model we begin by taking the linear approximation $\Phi\left(X\beta_U(h)\right) = \Phi\left(z\right) = 0.5 + X\gamma_U(h) + \varepsilon$, where $\gamma_U(h) = \left\{\sum_{j=0}^J \theta_j\left(z\right)\right\}\beta_U(h)$, $\theta_j\left(z\right) = \left(-1\right)^j z^{2j} \Big/ \sqrt{2\pi}(2j+1)2^j\, j!$, and the size of the approximation error ε can be made arbitrarily small through the appropriate choice of J

determining the order of the Maclaurin series expansion (see e.g. Olver et al., 2010).[3] Noting that all of the parameter values $\gamma_U(h)$ – including the intercept or 'constant' term – will vary across individuals, the detailed decomposition in this case may be written as:

$$S^I = 2\sum_{r=1}^{R}\sum_{r'=1}^{R} p_r p_{r'} \operatorname{sgn}\left(\Delta^I_{rr'}\right)\left(\sum_h P\left(H^I_r = h \mid R = r\right)\left(\overline{X_r \gamma^*_U(h)} - \overline{X_{r'} \gamma^*_U(h)}\right)\right) \qquad (7)$$

where the averages are taken over the products and $\gamma^*_U(h)$ is derived from $\gamma_U(h)$ in the same way as $\beta^*_U(h)$ from $\beta_U(h)$.

Finally, we note that estimation of a single set of link functions using the pooled national sample may result in biased estimates if regional identity is a significant explanatory factor (see Fortin et al., 2011). To check for possible bias in the resultant decompositions we also perform the indirect analysis based on an alternative estimator of $F_{H_U|X_U}(h \mid X = x)$. Specifically, we estimate a separate link function $F_{H_r|X_r}(h \mid X) = \Lambda\left(X\beta_r(h)\right)$ for each regional sub-sample and then construct the alternative estimator as a population-weighted average of the predictions from these models over the full national sample. The main problem with this approach is that if the probit link is chosen then some of the regional models may be prone to 'separation' or 'underidentification' for particular health states *h*, with one or more of the sociodemographic characteristics predicting one or other of the outcomes of the dependent variable perfectly (see Albert and Anderson, 1984). In this situation it is still possible to generate predictions for all observations, and the aggregate decomposition will therefore always be feasible, but not to obtain a full set of parameter estimates which is required for the detailed decomposition.

[3] Alternatively, the detailed decomposition could be performed using a Shapley-value procedure (Shorrocks, 2013) in which stratification due to the variation in each of the individual sociodemographic characteristics about the corresponding national average is eliminated in turn, with the final estimates obtained as averages over all possible elimination pathways.

3.2 Direct standardisation

The direct standardisation counterfactual is given by the distribution of health outcomes that would be observed if the (joint) distribution of sociodemographic characteristics in each region was the same as in the whole country. Following DiNardo et al. (1996), this may be written as:

$$\begin{aligned} F_{H_U^D}(h) &= \sum_{r=1}^{R} p_r F_{H_r^D}(h) = \sum_{r=1}^{R} p_r \left[\int F_{H_r|X_r}(h \mid X = x)\, dF_{X_U}(x) \right] \\ &= \sum_{r=1}^{R} p_r \left[\int F_{H_r|X_r}(h \mid X = x) \Psi_{Ur}(x)\, dF_{X_r}(x) \right] \end{aligned} \tag{8}$$

where $F_{H_U^D}(h)$ and $F_{H_r^D}(h)$ denote the national and regional counterfactual health distributions, and $\Psi_{Ur}(x) = dF_{X_U}(x) \big/ dF_{X_r}(x)$ may be interpreted as a set of observation-specific reweighting factors. Key to the validity of this approach is the assumption that the conditional distribution $F_{H_r|X_r}(h \mid X_r = x)$ would be the same if the marginal distribution of sociodemographic characteristics in region *r* was $F_{X_U}(x)$ rather than $F_{X_r}(x)$. Construction of $F_{H_U^D}(h)$ further requires $F_{X_r}(x)$ and $F_{X_U}(x)$ to have a common support for all regions.

We note that $F_{H_U^D}(h) = \sum_r p_r \left\{ \sum_{r'} p_{r'} \int F_{H_r|X_r}(h \mid X = x)\, dF_{X_{r'}}(x) \right\}$, since $dF_{X_U}(x) = \sum_{r'} p_{r'} dF_{X_{r'}}(x)$, and can therefore be seen as a population-weighted average of pairwise regional counterfactuals with each representing a 'simple counterfactual treatment' in the terminology of Fortin et al. (2011). The adoption of a multilateral rather than a bilateral approach considerably simplifies the analysis as only one set of reweighting factors needs to be constructed for each region. Specifically we obtain $\Psi_{Ur}(x) = P(R = r) \big/ P(R = r \mid X = x)$, i.e. the ratio of the unconditional population share of region *r* to the population share conditional upon sociodemographic characteristics, where $P(R = r \mid X = x)$ is estimated by a flexible multinomial logit model. Alternatively, $P(R = r \mid X = x)$ can be estimated non-parametrically by partitioning the sample into a finite number of 'cells' defined by sociodemographic characteristics *X* (e.g., cells might be defined by a combination of sex, age group and income class) and calculating population shares in each cell, where this procedure

produces the same results as the estimation of a conformably-specified saturated multinomial logit model. The set of counterfactual distributions $F_{H_r^D}(h)$ are calculated using $\Psi_{Ur}(x)$ for each region to reweight the relevant sample observations.

The counterfactual health distributions are used to construct the directly standardised pairwise indices $\Delta_{rr'}^D = \mathrm{P}\left(H_{r'}^D > H_r^D\right) - \mathrm{P}\left(H_r^D > H_{r'}^D\right)$ and the summary comparative health measures $\Delta_{Ur'}^D = \sum_r p_r \Delta_{rr'}^D$. The alternative, direct aggregate decomposition is defined as:

$$S = \sum_{r=1}^{R}\sum_{r'=1}^{R} p_r\, p_{r'} \left|\Delta_{rr'}\right| = \sum_{r=1}^{R}\sum_{r'=1}^{R} p_r\, p_{r'} \left\{\left|\Delta_{rr'}^D\right| + \left(\left|\Delta_{rr'}\right| - \left|\Delta_{rr'}^D\right|\right)\right\} = S^D + \left(S - S^D\right) \quad (9)$$

where the directly standardised index S^D may be interpreted as a headcount index of conditional health stratification, providing a measure of the 'unexplained' component of total health stratification due to conditional health differences. We note that if the multinomial logit model has no explanatory power then S^D=S, since $P\left(R = r \mid X = x\right) = P\left(R = r\right)$ for all x in this case, implying that all stratification is again due to conditional health differences between regions. The 'explained' component due to compositional differences is captured by the residual term ($S - S^D$), which may be either positive or negative. We do not attempt a detailed decomposition of this aggregate compositional effect in the absence of an explicit model of health in the direct standardisation approach.

4. Empirical analysis

We use the new measurement framework to investigate differences in adult population health between the regions of the United Kingdom (UK). Our empirical analysis makes use of data from both the Family Resources Survey (FRS: Department for Work and Pensions et al., 2016a) and Households Below Average Incomes (HBAI: Department for Work and Pensions, 2016b) for the financial year 2014-15. The FRS is an annual cross-sectional survey that collects information about the incomes and living circumstances of a representative sample of approximately 20000 private households in the UK. The FRS is considered to be foremost

source of evidence on UK household net income and poverty (Office for National Statistics, 2016), providing the primary data for both HBAI and EU-Statistics on Income and Living Conditions (EU-SILC).

The study is based on NUTS 1 statistical regions – Wales, Scotland, Northern Ireland and the nine Government Office Regions in England (see Figure 1). The analysis was limited to the HBAI sample to ensure that all observations had complete data on age, sex and income.[4] Sample weights were used throughout the analysis with these being given by SPI-adjusted HBAI grossing factors (Department for Work and Pensions, 2016c), modified when necessary to allow for missing health data using inverse probability weights (see Wooldridge, 2002). Standard errors for all health difference and stratification indices were generated using a bootstrap procedure that partially takes account of the stratified nature of the FRS sample design by resampling observations within each NUTS 1 region, but not of the full stratification design nor of clustering (in Great Britain) as regional stratifiers and Primary Sampling Unit identifiers are withheld in the standard End User Licence dataset to protect confidentiality. Computed standard errors may be biased downwards as a result.

4.1 Health measures

We considered two self-reported health measures in the study. FRS respondents were asked to say in general whether their health was very good, good, fair, bad or very bad (FRS variable: HEATHAD), from which we derived a self-assessed health variable SAH by inverting the numerical coding so that higher scores correspond to better outcomes. Information on all adults was also collected on whether they had any physical or mental health conditions or illnesses

[4] "Households containing a married adult whose spouse is temporarily absent, whilst within the scope of the FRS, are excluded from HBAI" (Department for Work and Pensions, 2016, p.15). There were 69 such households in the 2014/15 survey.

lasting or expected to last for 12 months or more (FRS variable: HEALTH1) and, if so, whether these conditions reduced their ability to carry out their day to day activities a lot, a little or not at all (FRS variable: CONDIT), from which a single variable LSC was derived taking a minimum value of one for those with a disability that reduced their activities a lot and a maximum of four for those without any longstanding condition. Self-reported measures provide insight into how individuals experience their own health, which is important for their well-being, and have been widely used in the health economics literature to explore the relationship between health and income (see, e.g. O'Donnell et al., 2015). Nevertheless, it should be borne in mind that such measures do not provide objective indicators of general health status, with a number of recent studies providing evidence that reporting biases may be correlated with income and other sociodemographic characteristics (see, e.g. Davillas et al., 2017).

Table 1 reports population proportions by region and response category for the two health measures, with these data being plotted in the accompanying Figures. Roughly 70% of the UK population assessed their own health as either 'good' or 'very good', and 10% as either 'bad' or 'very bad'. Similar proportions reported respectively no longstanding condition and a disability that reduced their daily activities a lot. For both measures, clear-cut comparisons between pairs of regions can only be made on the basis of first-order stochastic dominance in about half of all cases. Nevertheless, self-assessed health generally appears to have been better in London and neighbouring regions than in the rest of England, with London also standing out in terms of the low prevalence and severity of disabilities. Conversely, the North East and North West of England had unambiguously lower levels of general health than almost all other UK regions in terms of self-assessed health and longstanding conditions respectively.

4.2 Sociodemographic variables

Table 2 provides summary statistics for the common set of sociodemographic variables that were employed in the standardisation procedures. INCOME is given by the HBAI variable S_OE_BHC, which is defined as deflated, equivalised, SPI-adjusted, weekly household disposable income before housing costs (Department of Work and Pensions, 2016c). It is equal to the total weekly income of all household members after deductions of income tax and other contributions but before housing costs, with this total being deflated to reflect average survey-year prices and equivalised using the OECD scale to take account of household composition. 'Very rich' individuals in the FRS are assigned income levels derived from the Survey of Personal Incomes (SPI), as the latter are deemed to give a more accurate indication of the level of high incomes than the FRS. Individuals with zero recorded income were assigned a value of £1/week. AGE is the FRS AGE80 variable and records age in years at last birthday, top coded at 80 for confidentiality reasons. The sample includes all surveyed individuals aged 16 and over, unless defined as a dependent child. MALE is a dummy variable coded 1 for males. NONWHITE is an ethnicity dummy variable coded zero for whites and one otherwise from the FRS variable INDETH. The three qualification variables HIQ12, HIQ345 and HIQ678 are derived from the FRS highest academic or vocational qualification variable DVHIQUAL, with responses banded together using Regulated Qualifications Framework (RQF) levels (see GOV.UK, 2017) into four roughly equal sized groups: none and entry level (e.g. literacy and numeracy certificates) – the omitted category; levels 1 and 2 (e.g. lower secondary school qualifications); levels 3, 4 and 5 (e.g. upper secondary school and sub-degree qualifications); and levels 6, 7 and 8 (e.g. first and higher university degrees).

4.3 Empirical results

Table 3 presents the main results of the analysis, with Panel 3A1 reporting estimates of the unstandardized total headcount indices. The main estimate for self-assessed health SAH

implies that there was a 3.26% difference on average in the chances that the healthier of any randomly chosen pair was from the region with the better rather than the worse population health, with this rising to 3.61% conditional on the two individuals being from different regions. Alternatively, the latter figure may be interpreted as the population-weighted average value of the rank-biserial correlation (Cureton, 1956) between individual and population health across mutually distinct pairs of regions, which although small is nevertheless statistically significant.

Table 4A reports the full set of pairwise health difference indices for SAH. Thus, for example, the {NE, LO} entry of 0.103 implies that if one individual had been randomly chosen from each region then there was a 10.3% difference in the chances that the healthier of the pair would have been from London rather than the North East, with the Londoner healthier in 39.7% of such comparisons, the North Easterner in 29.5% and the pair being equally healthy in the remaining 30.8% of matches. The string of positive values in the {LO} column and of negative values in the {NE} column imply that self-assessed health was better in London and worse in the North East than in all other UK regions, although not all of the pairwise indices are significantly different from zero. More generally, the results provide a total ordering of regions with self-assessed health significantly better in London, Southern and Eastern England, Scotland and Northern Ireland than in Northern England, the Midlands and Wales.

Taking the population-weighted average of the pairwise indices in any column yields the summary measure $\Delta_{UK,col}$ of the population health of that region compared to the UK as a whole. For example, there was a 6.0% chance that a randomly chosen North Easterner would have been less rather than more healthy than a person chosen at random from anywhere in the UK (including the North East itself), while there was a 4.2% chance that a Londoner would have been more rather than less healthy in a similar comparison. The set of comparative health measures may in turn be used to calculate a conventional between-region slope inequality index

if regions are ranked in order of mean incomes, which yields a 6.20% difference in predicted chances between the richest and poorest in the UK as reported in Panel C of Table 3. This value may be compared with the normalised income-related stratification health index of 2.49% in Table 3B, which measures the mean difference in the probabilities that the healthier of any randomly chosen pair from two different regions will be from the richer rather than the poorer region from which they are drawn. Finally, we note that all of the regional indices S_r are positive by construction, but that the North East and Wales stand out in terms of their disproportionate contribution to the total index value of 0.326 given how poor their population health was compared to the UK as a whole.

Table 3A1 also presents the main estimate of the headcount index for the LSC health measure, with this implying a 4.92% average difference in the chances that the less disabled of any randomly chosen pair was from the region with the lower rather than higher prevalence and severity of longstanding conditions, with this rising to 5.44% conditional on the two individuals being from different regions. It would thus appear that there was greater regional stratification in longstanding conditions than in self-assessed health, though this may simply be a statistical artefact due to the particular definition of health states employed in the specification of the two measures. To explore the possible effect of health state categorisation on stratification, the indices were re-estimated with both measures recoded into three health states, where the categories were chosen such that the proportion of the UK population falling into each category was roughly the same for both variables.[5] The 'comparable partition' estimates reported in Table 3A2 are only marginally different from the main estimates, which provides some assurance that the difference between the SAH and LSC indices is not due to the arbitrary definition of health state categories but rather reflects substantive differences in the constructs underlying the two measures of health status.

[5] Specifically we combine categories 1 and 2, and 4 and 5 for SAH, and 2 and 3 for LSC.

Table 4B reports the pairwise indices for LSC. The most striking finding is that a randomly chosen Londoner was significantly more likely to have been less rather than more disabled than a randomly chosen individual from any other UK region, consistent with the first-order stochastic dominance results. As a result, the contribution of London to total disability stratification was 31.0% despite the region only accounting for 13.3% of the UK population. The results again provide a total ordering of regions with health on this measure significantly better in London, the South East and Northern Ireland than in virtually all other regions, and significantly worse in the North West and South West than in virtually all other regions. In the absence of a clear income gradient in disabilities, the Slope Inequality Index of 0.170 reported in Table 3C is less than the normalised income-related disability stratification index of 0.186 in 3B.

4.3.1 Indirect standardisation results

Table 3A2 reports estimates of the indirectly standardized headcount index S^I, with the preferred pooled probit estimate for SAH implying that the difference in the chances that the healthier of any randomly chosen pair was from the region with the better rather than the worse population health would only have been 2.05% on average if the conditional distribution of health had been the same in all UK regions as in the UK as a whole. Hence 63% (=0.0205/0.0326) of the stratification in self-assessed health was 'explained' by differences in sociodemographic composition between regions. Moreover the 'unexplained' residual of 37% was almost entirely due to systematic differences in the conditional health distributions, rather than non-zero average prediction errors, with the regional probit fitted estimates of the unstandardized indices given in Table 3A1 virtually indistinguishable from the main estimates. Both the LPM pooled and average regional probit estimates of S^I for SAH in Table 3A2 are close to the pooled probit estimate and thereby imply similar aggregate decompositions of the total index value into compositional and conditional health effects.

Table 5 reports the comparative UK-regional measures of unstandardized and indirectly standardised health, where the former are repeated from Table 4A and the latter are based on the health levels predicted by the pooled probit model given the sociodemographic composition of each region. We also report the differences between these two measures, which provide indirect estimates of the relative 'performance' of each regional health system in terms of population health outcome conditional upon sociodemographic characteristics. Thus, for example, the population health of London was significantly better than the UK as a whole because of the favourable sociodemographic composition of the region rather than any significant difference in conditional health outcomes. Conversely, the poor level of population health in the North East was not the result of significant sociodemographic disadvantage but rather of poor conditional health outcomes. More generally, population health was significantly better than would otherwise have been the case in London and the South East due to favourable sociodemographics, but significantly worse in the East and West Midlands, Wales and Northern Ireland. Conditional health outcomes were significantly better in the South West, Scotland and Northern Ireland than in the UK as a whole, and only significantly worse in the North East.

The estimates of the indirectly standardised stratification indices in Table 3A2 are broadly similar to the corresponding income-related indices reported in Table 3B, with the unnormalised income-related index for SAH implying that there was a 2.24% average difference in the chances that the healthier of any randomly chosen pair of individuals was from the more rather than less prosperous region from which they were drawn. However, this similarity is due more to chance than design. In particular, the income-related indices are not based on an explicit model of the relationship between individual health and sociodemographic characteristics and therefore fail to control for either conditional health effects or the confounding effects of sociodemographic characteristics other than income.

Table 6A reports the pooled probit regressions for SAH with the dummy dependent variable, which takes a value of one if the self-assessed health of the individual is no better than the stated category and zero otherwise, specified as a function of a quadratic in age, sex, ethnicity, the logarithm of income and highest qualification. The probability of having no better than fair or good health (i.e. $h \leq 3$ or $h \leq 4$) increased with age over the normal lifespan but the chances of being in bad or very bad health (i.e. $h \leq 1$ or $h \leq 2$) reached a peak at about 65-70 years old, presumably due to the effects of selective attrition beyond that age. Men were more likely than women to be in very bad heath but less likely to report no better than fair heath, while non-whites were more likely than whites to report having no better than either fair or good health. Higher incomes were associated with better outcomes across the whole of the health distribution, implying that the health profiles of higher income classes first-order stochastically dominated those of lower income classes. Education and training was similarly associated with better health outcomes compared to the omitted reference group of those with no or entry level qualifications, with the size of the effects greater for those with higher levels of qualifications. The pooled LPM results are broadly similar except in the lower tail of the health distribution (i.e. for $h \leq 1$) where the LPM estimates of the marginal effects are much smaller than the corresponding linearised pooled probit estimates.

Table 7 presents the results of the detailed decomposition analysis for SAH based on the linearized probit parameter estimates of the UK conditional health distribution model reported in Table 6A. The contribution of regional differences in the distribution of each factor to S^I reflects both the nature of the relationship between that factor and individual health as captured by the UK conditional health distribution model, and the association at the regional level between the factor and indirectly standardised population health as predicted by the model (cf. equation (7)). Thus age made a positive contribution to stratification because health was estimated to deteriorate as a function of age over most, if not necessarily all, of the lifespan and

older people were concentrated in regions with worse predicted population health given their overall sociodemographic composition. Sex had a negligible impact on stratification but ethnicity had a significant negative impact, which was due in large part to the high level of predicted health in London despite the exceptionally large proportion of non-white inhabitants for whom, ceteris paribus, the predicted chances of reporting no better than fair or good health were higher than whites. Income made a positive contribution to stratification given the unambiguously positive relationship between health and income and a tendency for more prosperous regions to have better predicted population health. But the size of this contribution was only 0.0036 after controlling for both conditional health effects and confounding factors, compared to the unnormalised income-related stratification index of 0.0224 reported in Table 3B. Education and training also had a positive impact on individual health but whereas regions with better indirectly standardised health tended to have a disproportionate number of inhabitants with university-level qualifications, those regions with worse indirectly standardised health had above average proportions of inhabitants with only lower secondary school qualifications or equivalent. By construction, the individual-specific intercept term was negatively correlated with predicted health levels from the pooled probit model. Table 7 also reports the detailed decomposition of S^I based on the pooled LPM model, with the results broadly similar once account is taken of the fact that the contribution of the constant in the LPM model was identically equal to zero.

The parallel results for LSC in Table 3A2 imply that 49% of total stratification in disability was explained by compositional differences, with an average 2.4% difference in the chances that the less disabled of any randomly chosen pair would have been from the region with less rather than more disabilities if the conditional distribution of disability had been the same in all UK regions. The pooled probit estimates for LSC presented in Table 5B show that the prevalence and severity of longstanding conditions was increasing at an increasing rate with

age over the whole of the lifespan, unambiguously lower for males and non-whites, and decreasing with both income and the highest level of qualifications. The detailed decomposition results in Table 7 show that the largest component of explained stratification was again due to regional differences in age composition: the prevalence and severity of longstanding conditions increased with age and regions with older populations were predicted to have higher levels of disability. Regional differences in sex composition played no significant role but ethnicity made a positive contribution to stratification since non-whites were less likely to report disability issues and were concentrated in regions, most notably London, predicted to have relatively low levels of disability given their sociodemographic composition. Income differences were predicted to have had a small significantly negative impact on stratification, although this result was reversed in the LPM detailed decomposition. University-level and lower secondary school qualifications made positive and negative contributions respectively, as for SAH, with the contribution of higher secondary school qualifications also significantly negative. Overall, the findings for LSC appear largely insensitive to the choice of link function used to generate the counterfactual health distribution.

4.3.2 Direct standardisation results

Table 3A3 reports estimates of the directly standardized headcount index S^D, with the preferred multinomial logit (MNL) estimates based on a model of regional identity with the same set of regresssors – age, age squared, sex, ethnicity, the logarithm of income and highest qualification – as the health distribution regressions. Thus the preferred estimate for SAH implies that the difference in the chances that the healthier of any randomly chosen pair was from the region with the better rather than the worse population health would have been 2.12% on average if the sociodemographic composition of all regions had been the same as the UK as a whole. By implication, 65% (=0.0212/0.0326) of stratification in self-assessed health was accounted for

by regional differences in conditional health outcomes, with the residual 35% due to regional differences in sociodemographic composition.

The direct standardisation estimates of the compositional and conditional health components of total health stratification are therefore almost exactly the reverse of the corresponding indirect standardisation estimates. Recall that both standardisation procedures will produce an estimate of the 'explained' share, due to regional differences in sociodemographic composition, equal to zero if the regression model fitted in the procedure has no explanatory power. We conjecture that the direct standardisation estimate of this share is biased downwards because regional identity was so poorly predicted by sociodemographic characteristics. Table 8 reports a pseudo-R^2 value of only 3.26% for the MNL model, despite the statistical significance of all the regressors, which is worse than the reported fit of any of the pooled probit models in Table 6A.

Table 3A3 also presents non-parametric estimates for SAH based on a classification of the population by HBAI grossing regime age band (see Department for Work and Pensions, 2016c), sex and income quintile. These imply that only 21.5% ((0.0326-0.0256)/0.0326) of health stratification was due to regional differences in sociodemographic composition, where this even lower estimate of the 'explained' share reflects the worse predictive power of the classification scheme with the pseudo-R^2 of the conformably-specified fully-saturated MNL model (results not reported) only 2.81%. Finally, the directly standardised estimates for LSC present a similar picture, with the preferred MNL estimate implying an 'explained' share of 30%, compared to the indirect standardisation estimate of 49%, and the non-parametric estimate an even lower share still.

5. Discussion

The paper develops a framework to investigate the association between regional health outcomes and socioeconomic characteristics that is directly applicable to the ordinal health and well-being data commonly available from general social surveys. The approach builds on the concept of statistical preference to motivate the choice of a measure of the difference in population health between pairs of regions that has a straightforward interpretation as the difference in the probabilities that the healthier of any randomly chosen pair of individuals is from the region with the better rather than the worse population health. The population-weighted average of the absolute values of these pairwise indices provides a total headcount stratification index that captures the extent to which the populations of different regions occupy well-defined strata in the national health distribution.

Socioeconomic inequalities in health are commonly evaluated using bivariate measures of association, with the proposal in Allanson (2017a) for an income-related health stratification index providing a recent contribution to this tradition. This paper offers a deeper analysis based on aggregate decomposition techniques that serve to identify how much of total headcount stratification is due to differences between regions in the joint distribution of a set of socioeconomic and demographic characteristics – age, sex, ethnicity, income and qualifications– and how much due to regional differences in individual health conditional upon those characteristics. The paper provides alternative estimators of the aggregate decomposition based on the construction of counterfactual distributions using either indirect or direct standardisation procedures, with the former based on the estimation of a distribution regression model of the UK conditional health distribution and the latter on a flexible multinomial logit model of regional identity. A straightforward extension of the indirect standardisation procedure yields detailed decomposition estimates of the individual contribution of regional differences in the distribution of each sociodemographic characteristic to stratification.

The measurement framework was used to investigate health stratification between the NUTS 1 regions of the United Kingdom in 2014/15. Unlike first-order stochastic dominance, the statistical preference relation provides a total ordering of regions for both health measures together with associated summary measures of the population health of each region compared to the UK as a whole. In particular, population self-assessed health in London, the South East, South West, Eastern England, Scotland and Northern Ireland was found to be significantly better than in the North East, North West, East and West Midlands, and Wales. Overall, there was a 3.26% difference in the chances that the healthier of any two individuals was from the region with the better rather than the worse population self-assessed health.

The low degree of pairwise stratification due to the overlapping of regional health distributions may be expected to have had the effect of obscuring systematic differences in population health between regions that might otherwise have been the object of greater public and policy concern. However, it should be noted that the results are sensitive to the chosen level of spatial aggregation. Aggregation over regions with widely differing levels of population health relative to the country as whole will tend to result in lower levels of health stratification. For example, a country-level analysis of health stratification between England, Wales, Scotland and Northern Ireland (results not reported) yielded estimates of headcount stratification below 1% for self-assessed health. Conversely, an analysis at the local district level would reveal localised pockets of health disadvantage within regions, which are partially masked in the current study based on regional health distributions. Perceptions of a North-South health divide within England recently led Public Health England to commission an independent inquiry into the issue (Whitehead, 2014).

The indirect and direct standardisation decomposition techniques produce contrasting estimates of the ‘explained’ and ‘unexplained’ components of total health stratification due to regional differences in sociodemographic composition and conditional health outcomes

respectively. We consider the indirect standardisation estimates to be more reliable because the direct standardisation estimates of the 'explained' share are likely biased downwards due to the poor explanatory power of the model of regional identity fitted in the procedure. Thus, our preferred estimate is that 63% of stratification in self-assessed health was attributable to regional variation in sociodemographic composition, with this factor largely accounting for the comparatively good population health of London and the South East and the relatively poor population health of the Midlands and Wales. Conversely, population health was good in the South West and Scotland and poor in the North East because of significantly different conditional health outcomes compared to the UK as whole. And the population health of Northern Ireland was relatively good despite the unfavourable sociodemographic composition of the region. Further work is required to understand the causes of the variation in conditional health outcomes across regions with a view to identifying potential health policy strategies to improve population health in the worst performing regions (cf. van Doorslaer and Koolman, 2004).

The detailed decomposition estimates reveal that regional differences in age, qualifications and income all contributed significantly to greater stratification in self-assessed health between regions. In particular, younger, better qualified and higher income individuals were more likely to have both reported better health and been concentrated in regions with better predicted population health according to the UK conditional health distributional model. However, the estimated contribution of regional differences in income distributions *per se* was much smaller than implied by the income-related stratification index for self-reported health, pointing more generally to the importance of taking account of conditional health effects and confounding factors in the evaluation of socioeconomic inequalities in population health between regions. Regional differences in ethnic mix moderated stratification because non-whites were more likely to report worse health but were particularly concentrated in the region,

London, with the best predicted population health conditional on sociodemographic composition.

The parallel results for longstanding conditions are broadly similar in nature but do reveal some notable differences in both the spatial pattern and severity of stratification in disabilities compared to self-assessed health, which might suggest that the UK has multiple health geographies warranting separate investigation (see also Allanson, 2017a). In particular, it would be of interest to explore patterns of regional stratification in other subjective measures of well-being – such as life satisfaction, meaningfulness, happiness and anxiety – and the extent to which these are associated with differences in sociodemographic composition. Further work is also required to examine the extent and drivers of changes in regional health stratification over time, with Whitehead (2014) emphasising the persistence of the root causes of observed differences in general health between regions. Finally, the measurement framework could be used to analyse differences between population groups classified on the basis of class, gender or race rather than region.

References

Albert, A., and J. A. Anderson (1984), On the Existence of Maximum Likelihood Estimates in Logistic Regression Models. *Biometrika* 71(1):1–10.

Allanson, P. (2017a) Monitoring income-related health differences between regions in Great Britain: A new measure for ordinal health data, *Social Science & Medicine*, 175, 72-80.

Allanson, P. (2017b) On the Measurement of the Overall Degree of Income Stratification between Groups, *Review of Income and Wealth*, doi: 10.1111/roiw.12290

Allison, R. A., & Forster, J. E. (2004). Measuring health inequality using qualitative data, *Journal of Health Economics*, 23, 505–524.

Chernozhukov, V. Fernández-Val, I., & Melly, B. (2013). Inference on counterfactual distributions, *Econometrica, 81*, 2205–2268.

Cureton, E. E. (1956). Rank-biserial correlation. *Psychometrika, 21*, 287-290.

Dagum, C. (1997) A New Approach to the Decomposition of the Gini Income Inequality Ratio, Empirical Economics, 22, 515–31.

Davillas; A., Jones, A.M. and M. Benzeval (2017). The income-health gradient: Evidence from self-reported health and biomarkers using longitudinal data on income. University of York Health Econometrics and Data Group WP/17/04. Retrieved from https://www.york.ac.uk/media/economics/documents/hedg/workingpapers/1704.pdf

De Baets, B., & De Meyer, H. (2007). Toward Graded and Nongraded Variants of Stochastic Dominance. In I. Batyrshin, L. Sheremetov and L. A. Zadeh (Eds.), *Perception-based Data Mining and Decision Making in Economics and Finance, Studies in Computational Intelligence* (Volume 36, pp.261–274). Berlin Heidelberg: Springer-Verlag.

De Baets, B., De Meyer, H., & De Loof, K. (2010). On the cycle-transitivity of the mutual rank probability relation of a poset. *Fuzzy Sets and Systems, 161*, 2695–2708.

De Schuymer, B., De Meyer, H., & De Baets, B. (2003). A fuzzy approach to stochastic dominance of random variables. In: T. Bildi, B. De Baets and O. Kaynak (Eds.), *Lecture Notes in Artificial Intelligence* (Volume 2715, pp.253–260). Berlin Heidelberg: Springer-Verlag.

Department for Work and Pensions, National Centre for Social Research and Office for National Statistics, Social and Vital Statistics Division (2016a) Family Resources Survey,

2014-2015 [computer file]. Colchester, Essex: UK Data Archive [distributor], July. SN: 8013, http://dx.doi.org/10.5255/UKDA-SN-8013-1.

Department for Work and Pensions, (2016b) Households Below Average Income, 1994/95-2014/15 [computer file]. 8th Edition. Colchester, Essex: UK Data Archive [distributor], July. SN: 5828 , http://dx.doi.org/10.5255/UKDA-SN-5828-6.

Department for Work and Pensions. (2016c). *Households below average income (HBAI): quality and methodology information report 2014/15*. Retrieved from https://www.gov.uk/government/statistics/households-below-average-income-199495-to-201415.

DiNardo, J., Fortin, N. M., & Lemieux, T. (1996). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica, 64*, 1001-44.

Dubois, D., Fargier, H., & Perny, P. (2003). Qualitative decision theory with preference relations and comparative uncertainty: An axiomatic approach. *Artificial Intelligence, 148*, 219–260.

Fortin, N.M., Lemieux, T. and Firpo, S. (2011). Decomposition methods in economics. In: O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics* (Volume 4, Part A, pp.1–102). Amsterdam: Elsevier North Holland.

GOV.UK (2017) *What qualification levels mean*. Retrieved from https://www.gov.uk/what-different-qualification-levels-mean/list-of-qualification-levels

Kobus, M. (2015). Polarization measurement for ordinal data. *Journal of Economic Inequality, 13*, 275-97.

Lasswell, T. E. (1965). Class and stratum. Boston: Houghton Mifflin.

Lieberson S (1976) Rank-sum comparisons between groups. *Sociological Methodology*, 7, 276–291.

Lv, G., Wang, Y., & Xu, Y. (2015). On a new class of measures for health inequality based on ordinal data. *Journal of Economic Inequality*, *13*, 465-77.

Marmot M., Allen J., Goldblatt P., Boyce T., McNeish D., Grady M., & Geddes I. (2010). *Fair society, healthy lives*: The Marmot review. Retrieved from http://www.instituteofhealthequity.org/projects/fair-society-healthy-lives-the-marmot-review.

O'Donnell, O., Van Doorslaer, E., & Van Ourti, T. (2015). Health and Inequality. In A. B. Atkinson and F. J. Bourguignon (Eds.), *Handbook of Income Distribution, Volume 2B* (pp. 1419-1533). Amsterdam: Elsevier.

Olver, F.W., Lozier, D.W., Boisvert, R.F. and Clark, C.W. (2010) *NIST Handbook of Mathematical Functions*. New York: Cambridge University Press.

Office for National Statistics. (2016). *A Guide to Sources of Data on Earnings and Income*. Retrieved from https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/methodologies/aguidetosourcesofdataonearningsandincome.

Shorrocks, A.F. (2013), Decomposition Procedures for Distributional Analysis: a Unified Framework Based on the Shapley value, *Journal of Economic Inequality*, 11(1), 99-126.

Taulbut M., Walsh D., Parcell S., Hartmann A., Poirier G., Strniskova D., Daniels G., & Hanlon P. (2013). What can ecological data tell us about reasons for divergence in health status between West Central Scotland and other regions of post-industrial Europe? *Public Health, 127*, 153-163.

Van Doorslaer, E and Koolman, X. (2004) Explaining the differences in income-related health inequalities across European countries. *Health Economics*, 13, 609–628

Whitehead M. (2014). *Due North: Report of the Inquiry on Health Equity for the North*. Retrieved from http://www.instituteofhealthequity.org/projects/due-north-the-report-of-the-inquiry-on-health-equity-for-the-north.

Wooldridge, J.M. (2002) *Econometric analysis of cross-section and panel data*. Cambridge, MA: MIT Press.

World Health Organization (1948) *Constitution of the World Health Organization*. Geneva: World Health Organization; 1948.

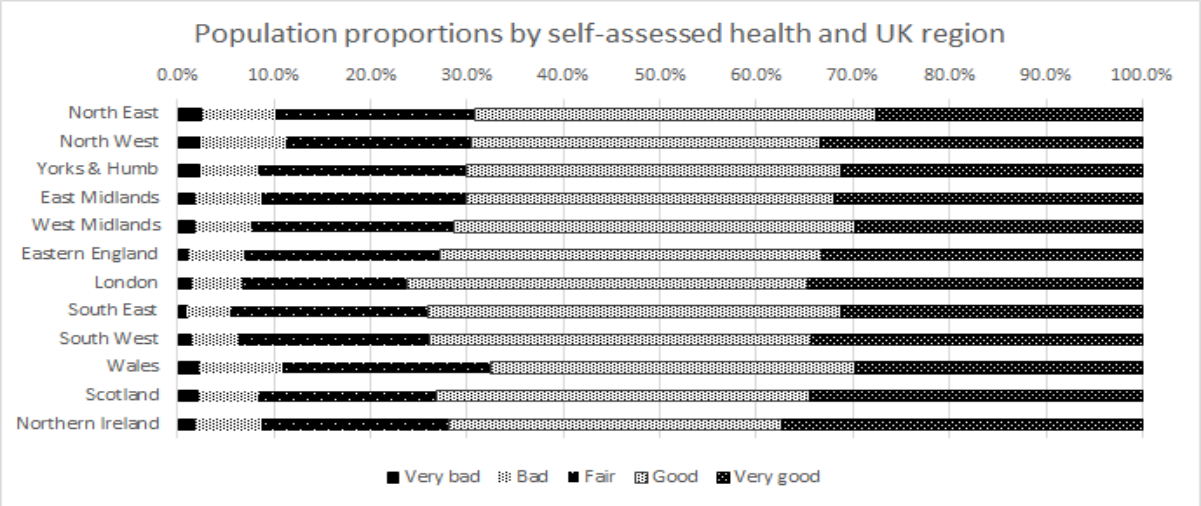
Zheng, B. (2011). A new approach to measure socioeconomic inequality in health. *Journal of Economic Inequality*, *9*, 555-577.

Figure 1: United Kingdom NUTS 1 statistical regions

Table 1: Population proportions by health status and region

Percentages	Self-assessed health - SAH					Longstanding condition - LSC			
	Very bad [1]	Bad [2]	Fair [3]	Good [4]	Very good [5]	Activities reduced a lot [1]	Activities reduced a little [2]	Activities not affected [3]	No condition [4]
North East	2.5	7.7	20.6	41.5	27.7	11.2	10.9	11.0	66.9
North West	2.4	8.8	19.3	36.1	33.4	13.3	12.7	11.3	62.8
Yorks & Humb	2.3	6.0	21.6	38.9	31.3	10.0	13.0	10.6	66.4
East Midlands	1.8	6.8	21.4	38.0	32.0	10.4	12.5	11.2	65.9
West Midlands	1.8	5.9	20.9	41.6	29.8	11.7	12.5	8.3	67.5
Eastern England	1.1	5.8	20.2	39.5	33.3	9.6	13.2	12.0	65.2
London	1.4	5.3	17.0	41.6	34.6	6.6	8.9	6.3	78.1
South East	0.9	4.5	20.5	42.8	31.3	8.3	12.5	10.8	68.4
South West	1.4	5.0	19.7	39.7	34.3	9.4	15.4	13.8	61.4
Wales	2.2	8.6	21.5	37.8	29.8	12.8	11.9	9.4	65.9
Scotland	2.1	6.2	18.6	38.7	34.5	11.1	12.7	10.5	65.6
Northern Ireland	1.7	6.9	19.5	34.5	37.3	13.2	8.9	4.0	73.8
United Kingdom	1.7	6.2	19.8	39.7	32.6	10.1	12.2	10.0	67.7

Source: own calculations, from HBAI and Family Resources Survey.



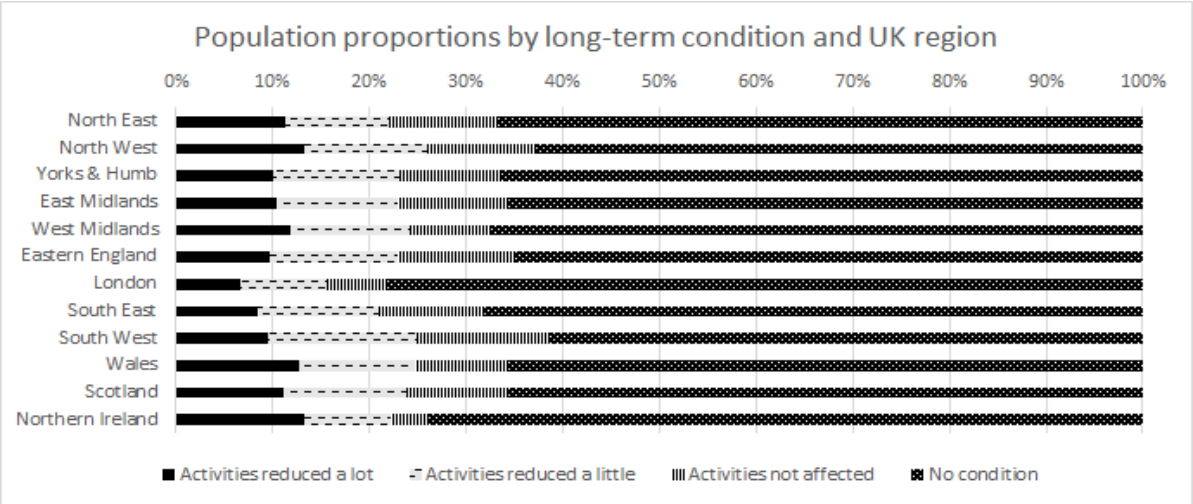


Table 2. Summary statistics by region – Sociodemographic variables

	Equiv hhold income	Age	Sex	Ethnicity	Highest RQF qualification level		
					1 or 2	3, 4 or 5	6, 7 or 8
Variable	INCOME	AGE	MALE	NWHITE	HIQ12	HIQ345	HIQ678
Region	*£/week*	*years*	%	%	%	%	%
North East	533.54	43.46	50.4	2.8	14.8	32.0	26.5
North West	569.51	45.19	49.7	9.2	23.3	26.2	24.9
Yorks & Humb	545.29	44.83	48.3	9.7	21.2	27.5	23.6
East Midlands	541.14	46.23	49.5	14.1	21.3	27.2	24.4
West Midlands	555.21	44.95	50.6	18.4	20.3	26.3	24.8
Eastern England	673.40	46.30	49.8	11.8	25.1	25.9	25.1
London	672.95	41.35	50.8	40.9	36.9	22.5	15.2
South East	705.01	45.89	49.6	8.8	27.1	29.5	22.2
South West	607.57	47.29	49.4	3.7	23.9	27.7	24.4
Wales	537.13	47.00	50.4	2.4	19.1	26.3	21.6
Scotland	579.65	45.46	48.6	3.3	19.9	35.2	18.6
Northern Ireland	502.25	44.10	49.9	1.6	18.5	25.0	24.9
United Kingdom	605.69	45.01	49.8	13.5	22.3	27.3	24.6

Source: Own calculations, from HBAI and Family Resources Survey.

Table 3. Health stratification indices

	Self-assessed health SAH		Longstanding condition LSC	
	Unnormalised	*Normalised*	*Unnormalised*	*Normalised*
3A Total health stratification indices				
3A1: Unstandardized indices	S	$\widehat{S}$	S	$\widehat{S}$
Main estimates	0.0326 **	0.0361 **	0.0492 **	0.0544 **
	0.0040	*0.0044*	*0.0027*	*0.0030*
'Comparable partition' estimates	0.0309 **	0.0342 **	0.0501 **	0.0554 **
	0.0033	*0.0037*	*0.0028*	*0.0031*
Regional probit fitted estimates	0.0326 **	0.0361 **	0.0491 **	0.0544 **
	0.0043	*0.0048*	*0.0028*	*0.0031*
3A2: Indirectly standardised indices	S^I	$\widehat{S}^I$	S^I	$\widehat{S}^I$
Pooled probit estimates	0.0205 **	0.0227 **	0.0243 **	0.0269 **
	0.0019	*0.0021*	*0.0013*	*0.0015*
Average regional probit estimates	0.0214 **	0.0237 **	0.0231 **	0.0256 **
	0.0019	*0.0021*	*0.0013*	*0.0014*
Pooled LPM estimates	0.0208 **	0.0230 **	0.0245 **	0.0272 **
	0.0019	*0.0021*	*0.0013*	*0.0014*
3A3: Directly standardised indices	S^D	$\hat{S}^D$	S^D	$\hat{S}^D$
'MNL' estimate	0.0212 **	0.0235 **	0.0343 **	0.0326 **
	0.0036	*0.0040*	*0.0031*	*0.0025*
'Saturated model' estimate	0.0256 **	0.0283 **	0.0380 **	0.0360 **
	0.0034	*0.0038*	*0.0034*	*0.0027*
3B: Income-related health stratification indices				
Unstandardized indices	0.0224 **	0.0249 **	0.0168 **	0.0186 **
	0.0042	*0.0046*	*0.0027*	*0.0030*
3C: Slope inequality indices				
Unstandardized indices		0.0620 **		0.0171
		0.0120		*0.0088*

*Source: Own calculations. Bootstrapped standard errors in italics based on 500 replications. Statistical significance at 1% and 5% levels are denoted by ** and * respectively.*

Table 4A: Detailed breakdown of the SAH headcount index by NUTS 1 Region

		Popn share	Pairwise health difference indices: $\Delta_{row,col} = \mathrm{P}\left(H_{col} > H_{row}\right) - \mathrm{P}\left(H_{row} > H_{col}\right)$												Regional index	Share of *S*
Region		%	NE	NW	YH	EM	WM	EE	LO	SE	SW	WA	SC	NI	S_{row}	%
North	NE	4.3	0	0.038	0.037	0.040	0.036	0.072**	0.103**	0.070**	0.087**	0.003	0.077**	0.088**	0.0026**	7.9
East			-	*0.021*	*0.021*	*0.022*	*0.021*	*0.020*	*0.021*	*0.021*	*0.022*	*0.025*	*0.019*	*0.020*	*0.0007*	
North	NW	11.2	-0.038	0	-0.002	0.002	-0.003	0.032*	0.060**	0.029	0.046**	-0.034	0.036**	0.048**	0.0030**	9.3
West			*0.021*	-	*0.016*	*0.017*	*0.016*	*0.015*	*0.016*	*0.015*	*0.017*	*0.020*	*0.014*	*0.017*	*0.0006*	
Yorks &	YH	8.1	-0.037	0.002	0	0.004	-0.001	0.035*	0.065**	0.032*	0.050**	-0.033	0.040**	0.052**	0.0024**	7.3
Humber			*0.021*	*0.016*	-	*0.017*	*0.016*	*0.016*	*0.016*	*0.015*	*0.018*	*0.020*	*0.014*	*0.017*	*0.0005*	
East	EM	6.9	-0.040	-0.002	-0.004	0	-0.005	0.031	0.061**	0.028	0.046*	-0.036	0.036*	0.048**	0.0019**	5.9
Midlands			*0.022*	*0.017*	*0.017*	-	*0.018*	*0.018*	*0.017*	*0.016*	*0.018*	*0.022*	*0.016*	*0.018*	*0.0005*	
West	WM	9.0	-0.036	0.003	0.001	0.005	0	0.036*	0.067**	0.033*	0.051**	-0.032	0.042**	0.053**	0.0027**	8.4
Midlands			*0.021*	*0.016*	*0.016*	*0.018*	-	*0.017*	*0.015*	*0.016*	*0.017*	*0.021*	*0.015*	*0.017*	*0.0006*	
East of	EE	8.9	-0.072**	-0.032*	-0.035*	-0.031	-0.036*	0	0.030	-0.003	0.015	-0.067**	0.006	0.018	0.0022**	6.9
England			*0.020*	*0.015*	*0.016*	*0.018*	*0.017*	-	*0.016*	*0.015*	*0.018*	*0.021*	*0.015*	*0.018*	*0.0004*	
London	LO	14.9	-0.103**	-0.060**	-0.065**	-0.061**	-0.067**	-0.030	0	-0.035*	-0.015	-0.097**	-0.024	-0.010	0.0062**	19.1
			0.021	*0.016*	*0.016*	*0.017*	*0.015*	*0.016*	-	*0.015*	*0.018*	*0.021*	*0.013*	*0.017*	*0.0014*	
South	SE	13.2	-0.070**	-0.029	-0.032*	-0.028	-0.033*	0.003	0.035*	0	0.019	-0.066**	0.010	0.022	0.0033**	10.2
East			*0.021*	*0.015*	*0.015*	*0.016*	*0.016*	*0.015*	*0.015*	-	*0.016*	*0.020*	*0.013*	*0.016*	*0.0004*	
South	SW	7.8	-0.087**	-0.046**	-0.050**	-0.046*	-0.051**	-0.015	0.015	-0.019	0	-0.082**	-0.009	0.004	0.0025**	7.6
West			*0.022*	*0.017*	*0.018*	*0.018*	*0.017*	*0.018*	*0.018*	*0.016*	-	*0.021*	*0.015*	*0.018*	*0.0006*	
Wales	WA	4.7	-0.003	0.034	0.033	0.036	0.032	0.067**	0.097**	0.066**	0.082**	0	0.072**	0.083**	0.0026**	8.0
			0.025	*0.020*	*0.020*	*0.022*	*0.021*	*0.021*	*0.021*	*0.020*	*0.021*	-	*0.019*	*0.021*	*0.0007*	
Scotland	SC	8.3	-0.077**	-0.036**	-0.040**	-0.036*	-0.042**	-0.006	0.024	-0.010	0.009	-0.072**	0	0.013	0.0022**	6.7
			0.019	*0.014*	*0.014*	*0.016*	*0.015*	*0.015*	*0.013*	*0.013*	*0.015*	*0.019*	-	*0.016*	*0.0004*	
Northern	NI	2.8	-0.088**	-0.048**	-0.052**	-0.048**	-0.053**	-0.018	0.010	-0.022	-0.004	-0.083**	-0.013	0	0.0009**	2.9
Ireland			*0.020*	*0.017*	*0.017*	*0.018*	*0.017*	*0.018*	*0.017*	*0.016*	*0.018*	*0.021*	*0.016*	-	*0.0003*	
Comparative health:			-0.060**	-0.020	-0.023	-0.019	-0.024*	0.012	0.042**	0.008	0.027*	-0.055**	0.017*	0.030*	-	
$\Delta_{UK,col}$			*0.017*	*0.011*	*0.012*	*0.013*	*0.012*	*0.011*	*0.010*	*0.008*	*0.012*	*0.018*	*0.009*	*0.012*	-	

See Table 3 for notes.

Table 4B: Detailed breakdown of the LSC headcount index by NUTS 1 Region

		Popn share	Pairwise health difference indices: $\Delta_{row,col} = \mathrm{P}\left(H_{col} > H_{row}\right) - \mathrm{P}\left(H_{row} > H_{col}\right)$												Regional index	Share of *S*
Region		%	NE	NW	YH	EM	WM	EE	LO	SE	SW	WA	SC	NI	S_{row}	%
North	NE	4.3	0.000	-0.045**	-0.003	-0.008	-0.001	-0.012	0.112**	0.020	-0.045**	-0.017	-0.014	0.049**	0.0014**	2.8
East				*0.013*	*0.014*	*0.015*	*0.014*	*0.014*	*0.013*	*0.013*	*0.015*	*0.017*	*0.013*	*0.013*	*0.0001*	
North	NW	11.2	0.045**	0.000	0.042**	0.038**	0.043**	0.035**	0.156**	0.066**	0.002	0.027	0.032**	0.091**	0.0058**	11.9
West			*0.013*		*0.011*	*0.012*	*0.011*	*0.011*	*0.009*	*0.010*	*0.012*	*0.015*	*0.009*	*0.011*	*0.0007*	
Yorks &	YH	8.1	0.003	-0.042**	0.000	-0.005	0.001	-0.008	0.116**	0.024*	-0.042**	-0.014	-0.010	0.052**	0.0026**	5.4
Humber			*0.014*	*0.011*		*0.013*	*0.012*	*0.012*	*0.010*	*0.011*	*0.013*	*0.015*	*0.010*	*0.011*	*0.0002*	
East	EM	6.9	0.008	-0.038**	0.005	0.000	0.006	-0.004	0.120**	0.029*	-0.037**	-0.010	-0.006	0.056**	0.0023**	4.6
Midlands			*0.015*	*0.012*	*0.013*		*0.012*	*0.013*	*0.012*	*0.012*	*0.014*	*0.016*	*0.011*	*0.012*	*0.0002*	
West	WM	9.0	0.001	-0.043**	-0.001	-0.006	0.000	-0.009	0.111**	0.022*	-0.042**	-0.015	-0.012	0.049**	0.0029**	5.8
Midlands			*0.014*	*0.011*	*0.012*	*0.012*		*0.012*	*0.010*	*0.011*	*0.013*	*0.015*	*0.010*	*0.011*	*0.0002*	
East of	EE	8.9	0.012	-0.035**	0.008	0.004	0.009	0.000	0.125**	0.032**	-0.034**	-0.006	-0.002	0.060**	0.0030**	6.2
England			*0.014*	*0.011*	*0.012*	*0.013*	*0.012*		*0.011*	*0.011*	*0.013*	*0.015*	*0.010*	*0.011*	*0.0003*	
London	LO	14.9	-0.112**	-0.156**	-0.116**	-0.120**	-0.111**	-0.125**	0.000	-0.093**	-0.160**	-0.127**	-0.125**	-0.057**	0.0152**	31.0
			0.013	*0.009*	*0.010*	*0.012*	*0.010*	*0.011*		*0.009*	*0.011*	*0.014*	*0.009*	*0.010*	*0.0009*	
South	SE	13.2	-0.020	-0.066**	-0.024*	-0.029*	-0.022*	-0.032**	0.093**	0.000	-0.067**	-0.038**	-0.034**	0.030**	0.0055**	11.2
East			*0.013*	*0.010*	*0.011*	*0.012*	*0.011*	*0.011*	*0.009*		*0.012*	*0.014*	*0.010*	*0.010*	*0.0006*	
South	SW	7.8	0.045**	-0.002	0.042**	0.037**	0.042**	0.034**	0.160**	0.067**	0.000	0.026	0.031**	0.092**	0.0042**	8.6
West			*0.015*	*0.012*	*0.013*	*0.014*	*0.013*	*0.013*	*0.011*	*0.012*		*0.016*	*0.011*	*0.012*	*0.0006*	
Wales	WA	4.7	0.017	-0.027	0.014	0.010	0.015	0.006	0.127**	0.038**	-0.026	0.000	0.004	0.064**	0.0016**	3.3
			0.017	*0.015*	*0.015*	*0.016*	*0.015*	*0.015*	*0.014*	*0.014*	*0.016*		*0.014*	*0.014*	*0.0003*	
Scotland	SC	8.3	0.014	-0.032**	0.010	0.006	0.012	0.002	0.125**	0.034**	-0.031**	-0.004	0.000	0.061**	0.0028**	5.7
			0.013	*0.009*	*0.010*	*0.011*	*0.010*	*0.010*	*0.009*	*0.010*	*0.011*	*0.014*		*0.010*	*0.0002*	
Northern	NI	2.8	-0.049**	-0.091**	-0.052**	-0.056**	-0.049**	-0.060**	0.057**	-0.030**	-0.092**	-0.064**	-0.061**	0.000	0.0017**	3.5
Ireland			*0.000*	*-0.045*	*-0.003*	*-0.008*	*-0.001*	*-0.012*	*0.112*	*0.020*	*-0.045*	*-0.017*	*-0.014*	*0.049*	*0.0002*	
Comparative health:			-0.008	-0.054**	-0.012	-0.016	-0.010	-0.020**	0.104**	0.012 *	-0.053**	-0.025 *	-0.022**	0.041**	-	
$\Delta_{UK,col}$			*0.011*	*0.007*	*0.009*	*0.009*	*0.008*	*0.008*	*0.006*	*0.006*	*0.009*	*0.012*	*0.006*	*0.008*	-	

See Table 3 for notes.

Table 5A. Pooled distribution regression results for self-assessed health SAH

	Pooled probit model				*Linearized pooled probit model*				*Pooled LPM*			
Health State	*h≤1*	*h≤2*	*h≤3*	*h≤4*	*h≤1*	*h≤2*	*h≤3*	*h≤4*	*h≤1*	*h≤2*	*h≤3*	*h≤4*
AGE	0.0407**	0.0478**	0.0326**	0.0236**	0.00883**	0.01359**	0.01178**	0.00884**	0.00101**	0.00437**	0.00658**	0.01078**
	0.0071	*0.0044*	*0.0031*	*0.0029*	*0.00153*	*0.00123*	*0.00106*	*0.00108*	*0.00023*	*0.00049*	*0.00082*	*0.00099*
AGE squared	-0.0003**	-0.0004**	-0.0001**	-0.0001*	-0.00007**	-0.00010**	-0.00005**	-0.00002*	-0.00001**	-0.00003**	-0.00001	-0.00005**
	0.0001	*0.0000*	*0.0000*	*0.0000*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.00000*	*0.00001*	*0.00001*	*0.00001*
MALE	0.0788*	0.0167	-0.0467**	-0.0247	0.01711*	0.00476	-0.01688**	-0.00924	0.00308*	0.00223	-0.01402**	-0.00842
	0.0369	*0.0232*	*0.0178*	*0.0180*	*0.00791*	*0.00655*	*0.00663*	*0.00707*	*0.00148*	*0.00311*	*0.00523*	*0.00607*
NWHITE	-0.1405	0.0664	0.1386**	0.1551**	-0.00618	0.01888	0.05010**	0.05806**	-0.00147	0.00796	0.03803**	0.05483**
	0.0148	*0.0402*	*0.0325*	*0.0308*	*0.01530*	*0.01097*	*0.01166*	*0.01185*	*0.00224*	*0.00516*	*0.00945*	*0.01035*
log(INCOME)	-0.0285**	-0.1710**	-0.1507**	-0.1533**	-0.03051**	-0.04859**	-0.05447**	-0.05740**	-0.00682**	-0.02557**	-0.04777**	-0.04865**
	0.0666	*0.0118*	*0.0119*	*0.0150*	*0.00309*	*0.00320*	*0.00422*	*0.00555*	*0.00113*	*0.00215*	*0.00386*	*0.00423*
HIQ678	-0.7206**	-0.6892**	-0.5498**	-0.4137	-0.15647**	-0.19585**	-0.19868**	-0.15489	-0.02794**	-0.09859**	-0.17584**	-0.13343**
	0.0657	*0.0390*	*0.0260*	*0.0282*	*0.01460*	*0.01044*	*0.00880*	*0.00991*	*0.00254*	*0.00520*	*0.00810*	*0.00897*
HIQ345	-0.3913**	-0.3989**	-0.3248**	-0.2875**	-0.08497**	-0.11336**	-0.11737**	-0.10763**	-0.02193**	-0.07367**	-0.11744**	-0.08576**
	0.0509	*0.0318*	*0.0246*	*0.0277*	*0.01087*	*0.00885*	*0.00882*	*0.01000*	*0.00261*	*0.00527*	*0.00810*	*0.00867*
HIQ12	-0.2767**	-0.2706**	-0.1702**	-0.1514**	-0.06008**	-0.07691**	-0.06151**	-0.05667**	-0.01894**	-0.06014**	-0.07099**	-0.03672**
	0.0504	*0.0314*	*0.0250*	*0.0288*	*0.01100*	*0.00902*	*0.00854*	*0.01020*	*0.00288*	*0.00572*	*0.00869*	*0.00877*
Intercept	-2.2001**	-1.4917**	-0.5991**	0.7466**	0.02227**	0.07607**	0.28349**	0.77955**	0.04649**	0.16454**	0.38472**	0.67679**
	0.2045	*0.1317*	*0.0995*	*0.1133*	*0.04496*	*0.03825*	*0.03470*	*0.04169*	*0.00773*	*0.01602*	*0.02910*	*0.03576*
n	33728	33728	33728	33728	-	-	-	-	33728	33728	33728	33728
Pseudo R^2	0.0838	0.0949	0.1033	0.0749	-	-	-	-	-	-	-	-

*Source: Own calculations. The linearized values are sample weighted averages of the individual-specific coefficient values obtained from the Maclaurin series expansion with J=30, which serves to reduce the size of the approximation errors in the detailed decompositions of S^I reported in Table 6 to the order of 10^{-7} or less. Bootstrapped standard errors for linearized estimates based on 500 replications. Statistical significance at 1% and 5% levels are denoted by ** and *.*

Table 5B. Pooled distribution regression results for self-assessed health LSC

	Pooled probit model			*Linearized pooled probit model*			*Pooled LPM*		
Health State	*h≤1*	*h≤2*	*h≤3*	*h≤1*	*h≤2*	*h≤3*	*h≤1*	*h≤2*	*h≤3*
AGE	0.0037	0.0069**	0.0154**	0.00110	0.00237**	0.00563**	-0.00357**	-0.00332**	0.00101
	0.0030	*0.0025*	*0.0023*	*0.00086*	*0.00082*	*0.00083*	*0.00048*	*0.00062*	*0.00068*
AGE squared	0.0001**	0.0001**	0.0001**	0.00004**	0.00005**	0.00004**	0.00007**	0.00010**	0.00008**
	0.0000	*0.0000*	*0.0000*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.00001*	*0.00001*
MALE	-0.0667**	-0.1061**	-0.0430**	-0.01961**	-0.03662**	-0.01574**	-0.01252**	-0.02851**	-0.01334**
	0.0182	*0.0152*	*0.0142*	*0.00546*	*0.00509*	*0.00508*	*0.00282*	*0.00392*	*0.00439*
NWHITE	-0.0046	-0.0843**	-0.2062**	-0.00136	-0.02910**	-0.07550**	-0.00335	-0.02075**	-0.05836**
	0.0304	*0.0249*	*0.0232*	*0.00909*	*0.00850*	*0.00846*	*0.00423*	*0.00577*	*0.00636*
log(INCOME)	-0.1922**	-0.1741**	-0.1216**	-0.05652**	-0.06008**	-0.04452**	-0.03158**	-0.04889**	-0.04050**
	0.0105	*0.0106*	*0.0102*	*0.00292*	*0.00348*	*0.00385*	*0.00209*	*0.00308*	*0.00337*
HIQ678	-0.7649**	-0.5220**	-0.3137**	-0.22496**	-0.18011**	-0.11488**	-0.12106**	-0.14342**	-0.10046**
	0.0290	*0.0227*	*0.0211*	*0.00828*	*0.00771*	*0.00767*	*0.00464*	*0.00632*	*0.00693*
HIQ345	-0.4864**	-0.3488**	-0.1940**	-0.14305**	-0.12036**	-0.07103**	-0.09925**	-0.11003**	-0.06587**
	0.0259	*0.0213*	*0.0204*	*0.00742*	*0.00725*	*0.00752*	*0.00487*	*0.00631*	*0.00681*
HIQ12	-0.3201**	-0.2405**	-0.1512**	-0.09414**	-0.08298**	-0.05537**	-0.07859**	-0.08477**	-0.05451**
	0.0257	*0.0218*	*0.0210*	*0.00773*	*0.00793*	*0.00789*	*0.00517*	*0.00668*	*0.00715*
Intercept	-0.2999**	-0.0970	-0.5065**	0.41180**	0.46654**	0.31456**	0.37998**	0.54318**	0.40425**
	0.0952	*0.0849*	*0.0814*	*0.02694*	*0.02803*	*0.02943*	*0.01564*	*0.02249*	*0.02524*
n	45237	45237	45237	-	-	-	45237	45237	45237
Pseudo R^2	0.1297	0.1248	0.1289	-	-	-	-	-	-

See Table 5A for notes.

Table 6. Detailed decomposition of indirectly standardised headcount indices S^I

	Self-assessed health SAH					Longstanding condition LSC				
Counterfactual	*Pooled probit*	*Share of S^I*	*Pooled LPM*	*Share of S^I*	*Av. Reg. probit*	*Pooled probit*	*Share of S^I*	*Pooled LPM*	*Share of S^I*	*Av. Reg. probit*
Explained effect S^I	0.0205 **		0.0208 **		0.0214 **	0.0243 **		0.0245 **		0.0231 **
	0.0019		*0.0019*		*0.0019*	*0.0013*		*0.0013*		*0.0013*
of which due to: AGE	0.0291 **	*141.9%*	0.0182 **	*87.5%*	-	0.0093 **	38.4%	-0.0009	-3.7%	-
	0.0042		*0.0029*			*0.0021*		*0.0010*		
AGE squared	-0.0121 **	*-58.8%*	-0.0066 **	*-31.7%*	-	0.0082 **	34.0%	0.0135 **	54.8%	-
	0.0024		*0.0017*			*0.0016*		*0.0017*		
MALE	0.0001	*0.3%*	0.0001	*0.3%*	-	-0.0001	-0.2%	0.0001	0.4%	-
	0.0001		*0.0001*			*0.0001*		*0.0001*		
NWHITE	-0.0052 **	*-25.3%*	-0.0044 **	*-21.2%*	-	0.0063 **	25.9%	0.0051 **	21.0%	-
	0.0010		*0.0008*			*0.0010*		*0.0008*		
log(INCOME)	0.0036 **	*17.8%*	0.0049 **	*23.4%*	-	-0.0013 *	-5.3%	0.0031 **	12.5%	-
	0.0011		*0.0009*			*0.0006*		*0.0006*		
HIQ678	0.0143 **	*69.9%*	0.0120 **	*57.9%*	-	0.0072 **	29.7%	0.0066 **	26.7%	-
	0.0016		*0.0013*			*0.0008*		*0.0007*		
HIQ345	-0.0011	*-5.4%*	-0.0008	*-3.8%*	-	-0.0019 **	-7.8%	-0.0015 **	-6.0%	-
	0.0011		*0.0008*			*0.0005*		*0.0004*		
HIQ12	-0.0032 **	*-15.4%*	-0.0026 **	*-12.5%*	-	-0.0015 **	-6.4%	-0.0014 **	-5.7%	-
	0.0005		*0.0004*			*0.0003*		*0.0003*		
Intercept	-0.0051 **	*-25.0%*	0.0000	*0.0%*	-	-0.0020 **	-8.3%	0.0000	0.0%	-
	0.0005		*0.0000*			*0.0004*		*0.0000*		

See Table 3 for notes.

Table 7: UK-regional comparative health

	Self-assessed health - SAH			Longstanding condition - LSC		
Region	$\Delta_{UK,row}$	$\Delta^{I}_{UK,row}$	Difference	$\Delta_{UK,row}$	$\Delta^{I}_{UK,row}$	Difference
North	-0.060 **	0.005	-0.065 **	-0.008	-0.008	0.000
East	*0.017*	*0.007*	*0.019*	*0.011*	*0.005*	*0.012*
North	-0.020	-0.002	-0.018	-0.054 **	-0.008 **	-0.045 **
West	*0.011*	*0.004*	*0.011*	*0.007*	*0.003*	*0.007*
Yorks &	-0.023	-0.006	-0.017	-0.012	-0.008 *	-0.003
Humber	*0.012*	*0.005*	*0.013*	*0.009*	*0.003*	*0.009*
East	-0.019	-0.020 **	0.001	-0.016	-0.016 **	0.000
Midlands	*0.013*	*0.005*	*0.013*	*0.009*	*0.004*	*0.010*
West	-0.024 *	-0.022 **	-0.002	-0.010	-0.005	-0.005
Midlands	*0.012*	*0.004*	*0.013*	*0.008*	*0.003*	*0.008*
East of	0.012	-0.004	0.016	-0.020 **	-0.005	-0.014
England	*0.011*	*0.004*	*0.013*	*0.008*	*0.003*	*0.008*
London	0.042 **	0.036 **	0.006	0.104 **	0.058 **	0.045 **
	0.010	*0.005*	*0.011*	*0.006*	*0.003*	*0.007*
South	0.008	0.013 **	-0.005	0.012 *	0.002	0.010
East	*0.008*	*0.004*	*0.009*	*0.006*	*0.003*	*0.007*
South	0.027 *	-0.008	0.035 **	-0.053 **	-0.023 **	-0.031 **
West	*0.012*	*0.005*	*0.013*	*0.009*	*0.004*	*0.010*
Wales	-0.055 **	-0.031 **	-0.024	-0.025 *	-0.039 **	0.013
	0.018	*0.007*	*0.019*	*0.012*	*0.005*	*0.013*
Scotland	0.017 *	-0.003	0.020 *	-0.022 **	-0.012 **	-0.010
	0.009	*0.004*	*0.009*	*0.006*	*0.003*	*0.007*
Northern	0.030 *	-0.016 **	0.045 **	0.041 **	-0.011 **	0.051 **
Ireland	*0.012*	*0.005*	*0.014*	*0.008*	*0.004*	*0.009*

See Table 3 for notes.

Table 8. Multinomial logit regression results for self-assessed health SAH

Region / *Variable*	*NE*	*NW*	*YH*	*EM*	*WM*	*EE*	*SE*	*SW*	*WA*	*SC*	*NI*
AGE	-0.0545**	-0.0018**	-0.0160**	0.0105**	0.0047**	0.0001	-0.0026**	-0.0062**	0.0099**	0.0044**	0.0097**
	0.0002	*0.0002*	*0.0002*	*0.0002*	*0.0002*	*0.0002*	*0.0001*	*0.0002*	*0.0002*	*0.0002*	*0.0002*
AGE squared	0.0006**	0.0001**	0.0003**	0.0000**	0.0001**	0.0002**	0.0002**	0.0003**	0.0000**	0.0001**	-0.0001**
	0.0000	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
MALE	0.0201**	0.0124**	-0.0633**	-0.0179**	0.0276**	-0.0092**	-0.0288**	-0.0311**	0.0378**	-0.0594**	0.0069**
	0.0013	*0.0010*	*0.0011*	*0.0011*	*0.0010*	*0.0010*	*0.0009*	*0.0011*	*0.0013*	*0.0011*	*0.0016*
NWHITE	-3.8118**	-1.9040**	-1.8468**	-1.5919**	-1.1054**	-1.4676**	-1.8407**	-2.6472**	-3.4382**	-2.8133**	-3.9816**
	0.0048	*0.0014*	*0.0016*	*0.0016*	*0.0013*	*0.0014*	*0.0014*	*0.0023*	*0.0040*	*0.0023*	*0.0064*
log(INCOME)	-0.5506**	-0.5085**	-0.4795**	-0.4432**	-0.4685**	-0.1490**	-0.1118**	-0.3170**	-0.5485**	-0.4673**	-0.5886**
	0.0009	*0.0007*	*0.0008*	*0.0008*	*0.0008*	*0.0009*	*0.0008*	*0.0009*	*0.0009*	*0.0008*	*0.0010*
HIQ678	-0.5458**	0.0635**	-0.2009**	-0.1400**	-0.2891**	-0.0115**	0.2565**	0.2230**	-0.3870**	-0.2258**	-0.5763**
	0.0022	*0.0015*	*0.0016*	*0.0017*	*0.0015*	*0.0016*	*0.0014*	*0.0017*	*0.0019*	*0.0016*	*0.0024*
HIQ345	0.6713**	0.6723**	0.6028**	0.6835**	0.3771**	0.6145**	0.9143**	0.8636**	0.4207**	0.8990**	0.2069**
	0.0020	*0.0015*	*0.0016*	*0.0017*	*0.0015*	*0.0016*	*0.0015*	*0.0017*	*0.0019*	*0.0016*	*0.0023*
HIQ12	0.6065**	0.6741**	0.6233**	0.7338**	0.6077**	0.7790**	0.7767**	0.8708**	0.2814**	0.2958**	0.4182**
	0.0021	*0.0016*	*0.0017*	*0.0018*	*0.0016*	*0.0016*	*0.0016*	*0.0018*	*0.0020*	*0.0018*	*0.0023*
Intercept	3.4948**	2.7582**	2.7069**	1.5302**	2.2186**	0.1159**	0.2049**	1.0291**	2.1665**	2.2146**	2.2493**
	0.0070	*0.0055*	*0.0060*	*0.0064*	*0.0058*	*0.0063*	*0.0057*	*0.0064*	*0.0069*	*0.0061*	*0.0080*
	n=72156459				*Pseudo* R^2=0.0326						

*Source: Own calculations. London is the base outcome. Statistical significance at 1% and 5% levels are denoted by ** and *.*